



An Objectively Optimized Earth Observing System

A10P1 Session A10: Task Planning in Sensor Webs

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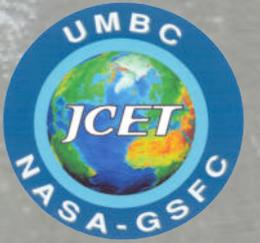
UMBC/JCET NASA/GSFC

Big Picture



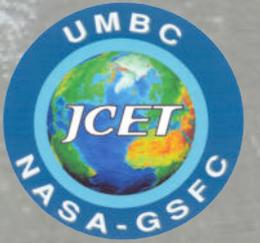
- It is of great utility to optimize:
 - Observing schedules.
 - Overall design of the missions and instruments.
- We need to deal with biases as part of our sensor web architecture.

Autonomy



- To make a system autonomous we need criteria and a methodology to guide/provide the autonomy in real time.
- For Unmanned Aerial Vehicles (UAVs) the sophistication of autonomy has been growing over the last twenty years. The methodologies used include:
 - optimization
 - information theory
 - computer vision
 - mixed integer linear programming
 - fuzzy logic
 - genetic algorithms
 - artificial cognition
 - geographic information systems (GIS)
 - set partition theory
 - vehicle health status
 - threat assessments

Previous Uses of Autonomy



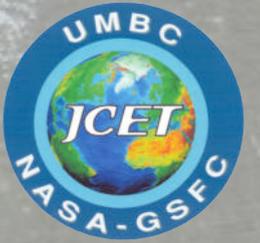
- The existing autonomous UAVs (aircraft or helicopter) are advanced and complex robotics platforms used for a variety of tasks. For example, UAVs can be used for:
 - environmental monitoring (weather and/or pollution)
 - traffic monitoring
 - surveillance
 - intelligence gathering
 - terrain mapping
 - emergency services assistance
 - studying the movement of agricultural threat agents, pollen, plant pathogens, and other biological particles
 - crop condition
 - photogrammetry
 - surveying

A Suite of Assets



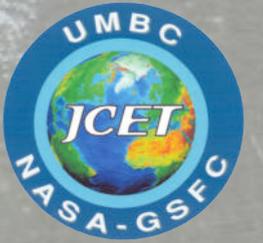
- The autonomy may be for an individual asset acting alone or for a suite of assets working together.
- The assets may be of different kinds, UAVs, Unmanned Ground Vehicles (UGVs), Underwater Unmanned Vehicles (UUVs), and Unattended Ground Sensors (UGS).
- The tasks/goals may, or may not, have been defined a priori.

Sensor Web Autonomy



- In the case of sensor webs for earth observation we also have a suite of assets: orbital, sub orbital (aircraft, UAVs, balloon sondes, long-duration balloons, UUVs), and ground based.
- There are also a variety of measurement types and a variety of purposes for these measurements, not all of which are known a priori.
- In addition, a given sensor may have a variety of modes of operation.
- The observations may have significant power and communication requirements associated with them.

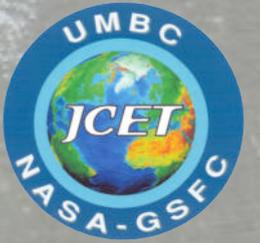
Underlying Principle



The knowledge of ignorance is
the beginning of knowledge

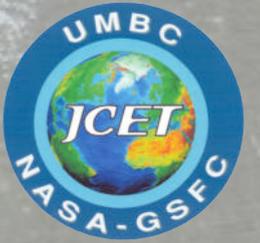
Ancient Greek Saying

Situational Awareness



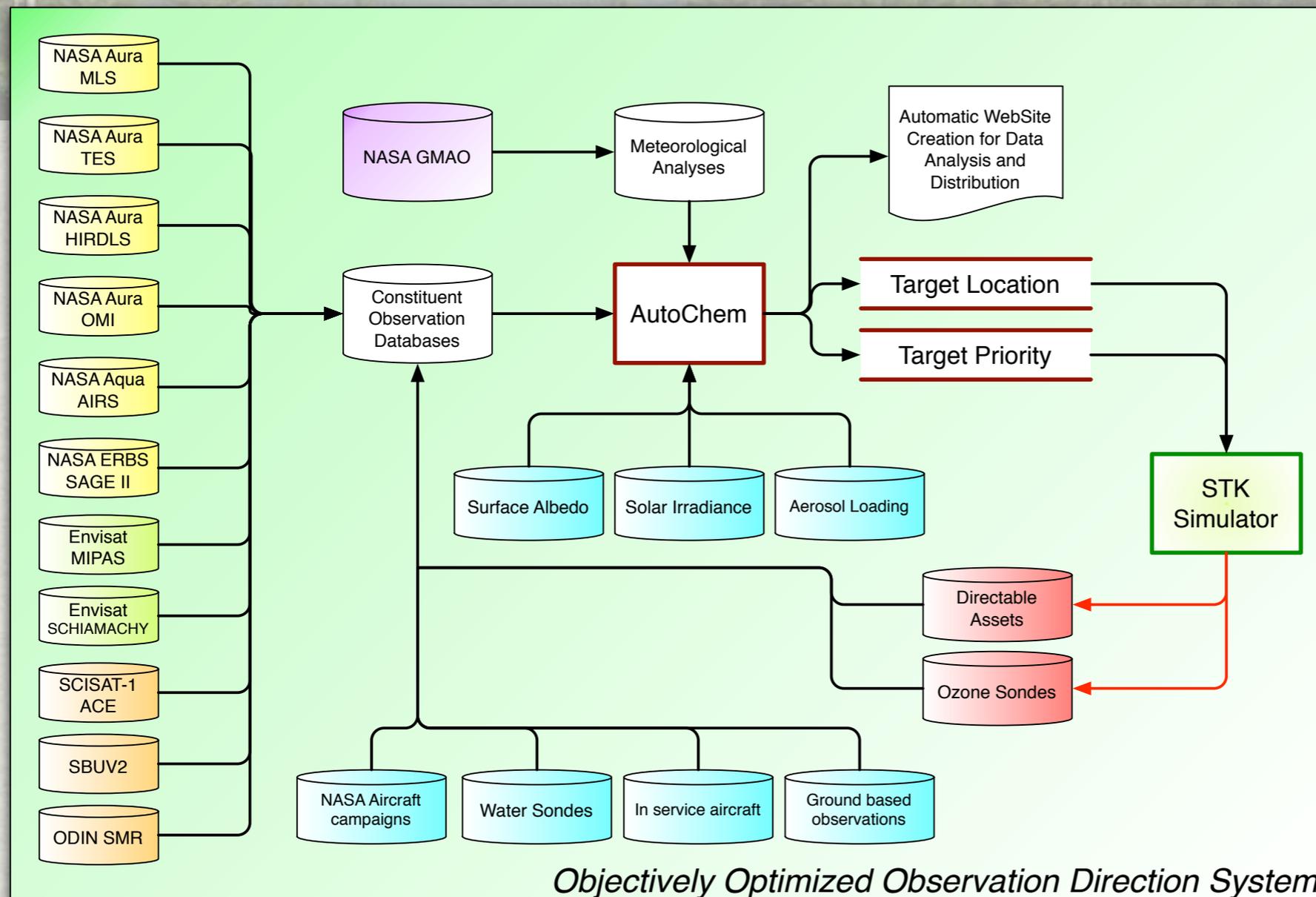
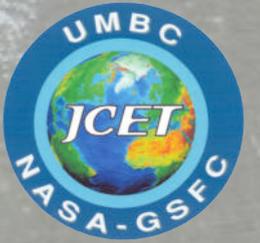
- In our project we are adding **situational awareness** via incorporation of our theoretical and observational understanding.
- The theoretical understanding is provided by a **deterministic model** of the system being observed.
- The observational understanding is provided by prior sensor web observations incorporated through a **data assimilation** system (in this case a full Kalman filter).
- The autonomy is provided by **objective optimization**.

Target Selection



- Metrics of **what we do not know** (state vector uncertainty) are used to define what we need to measure and the required mode, time and location of the observations, i.e. to define in real time the observing system targets.
- Metrics of **how important it is** to know this information (information content) are used to assign a priority to each observation.
- The metrics are passed in real time to the Sensor Web observation scheduler to implement the observation plan for the next observing cycle.

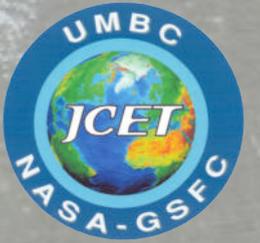
Modeling and Assimilation System Engineering Diagram



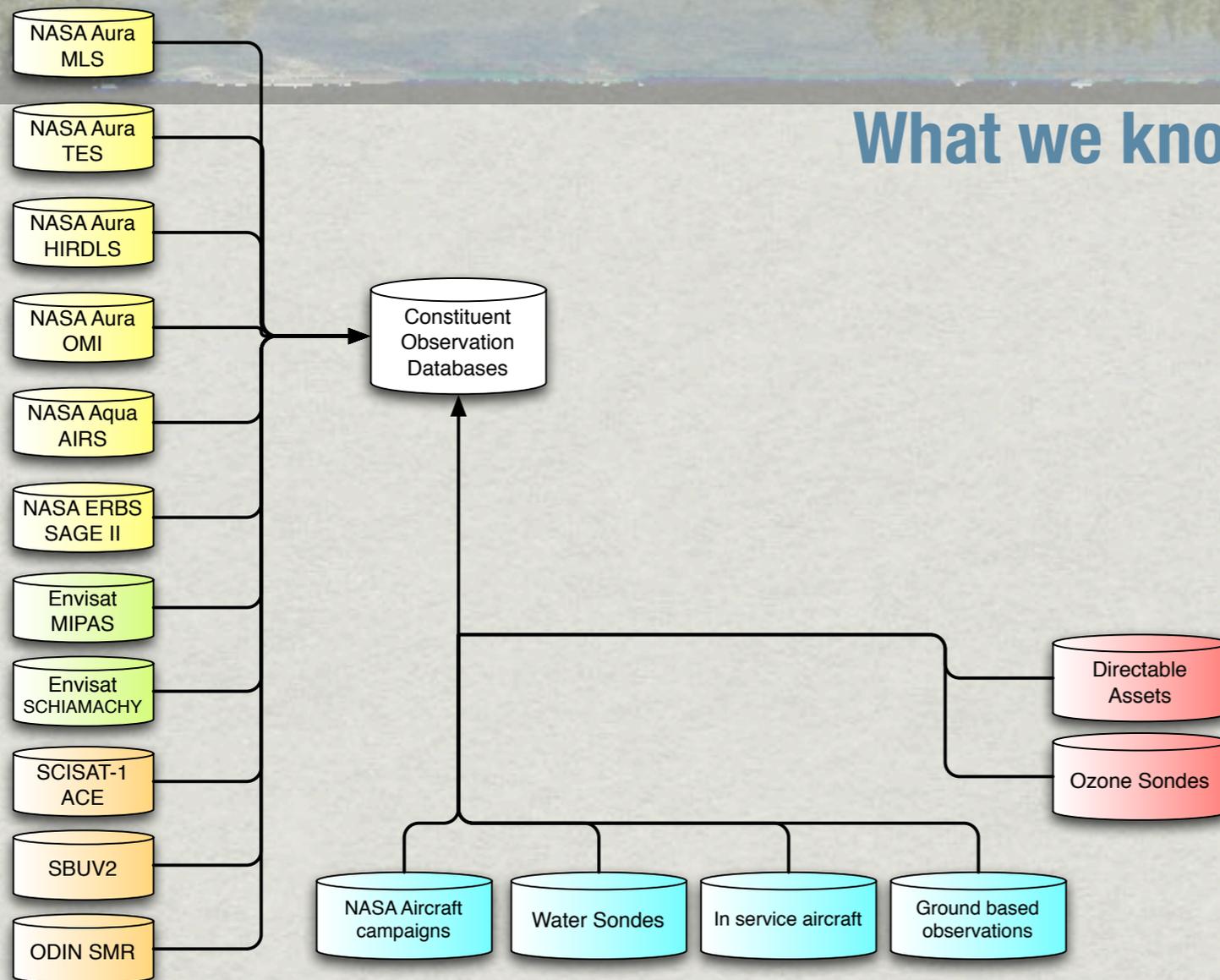
Objectively Optimized Observation Direction System

Modeling and Assimilation System Engineering Diagram

Data Query



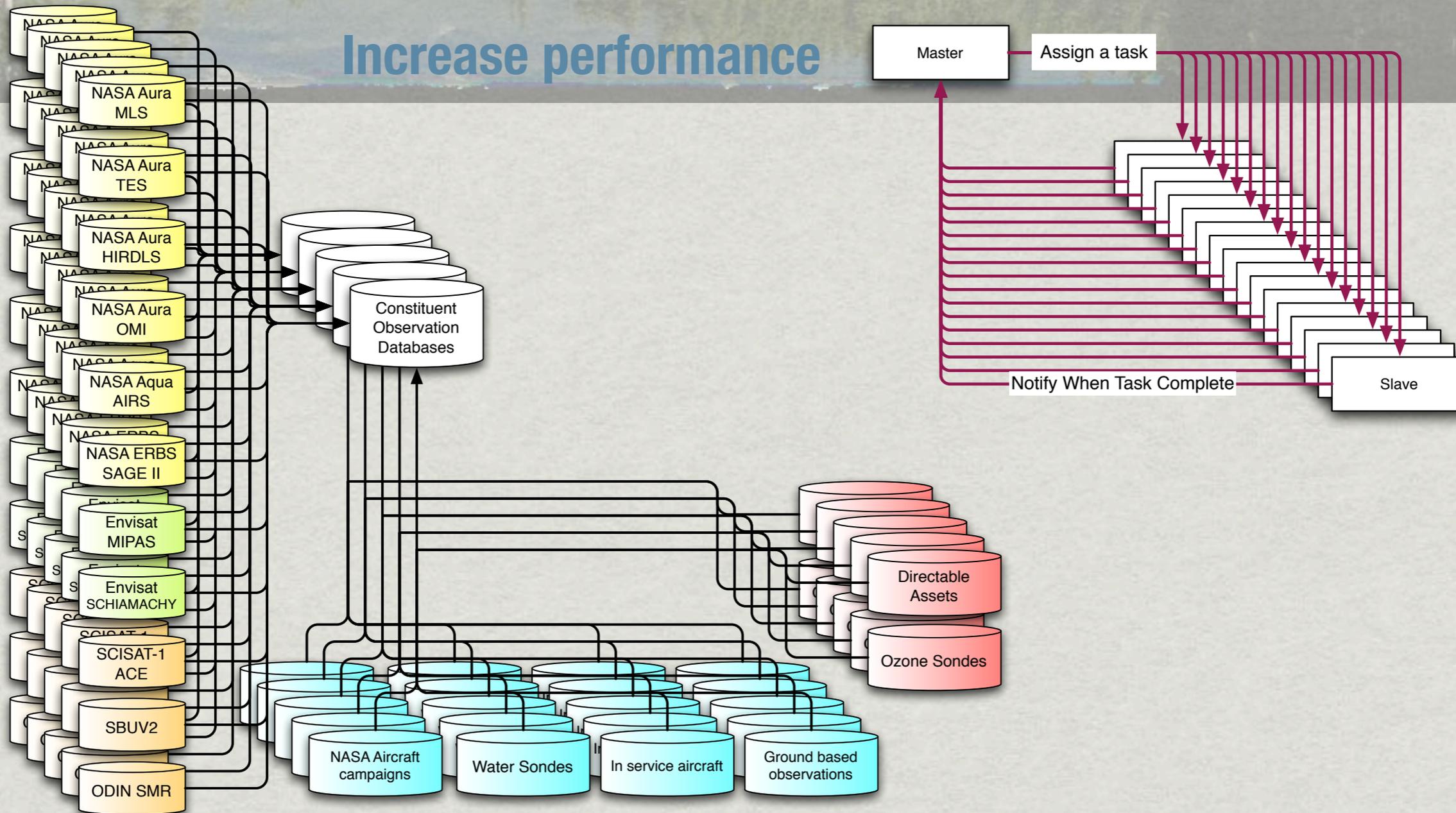
What we know from observations



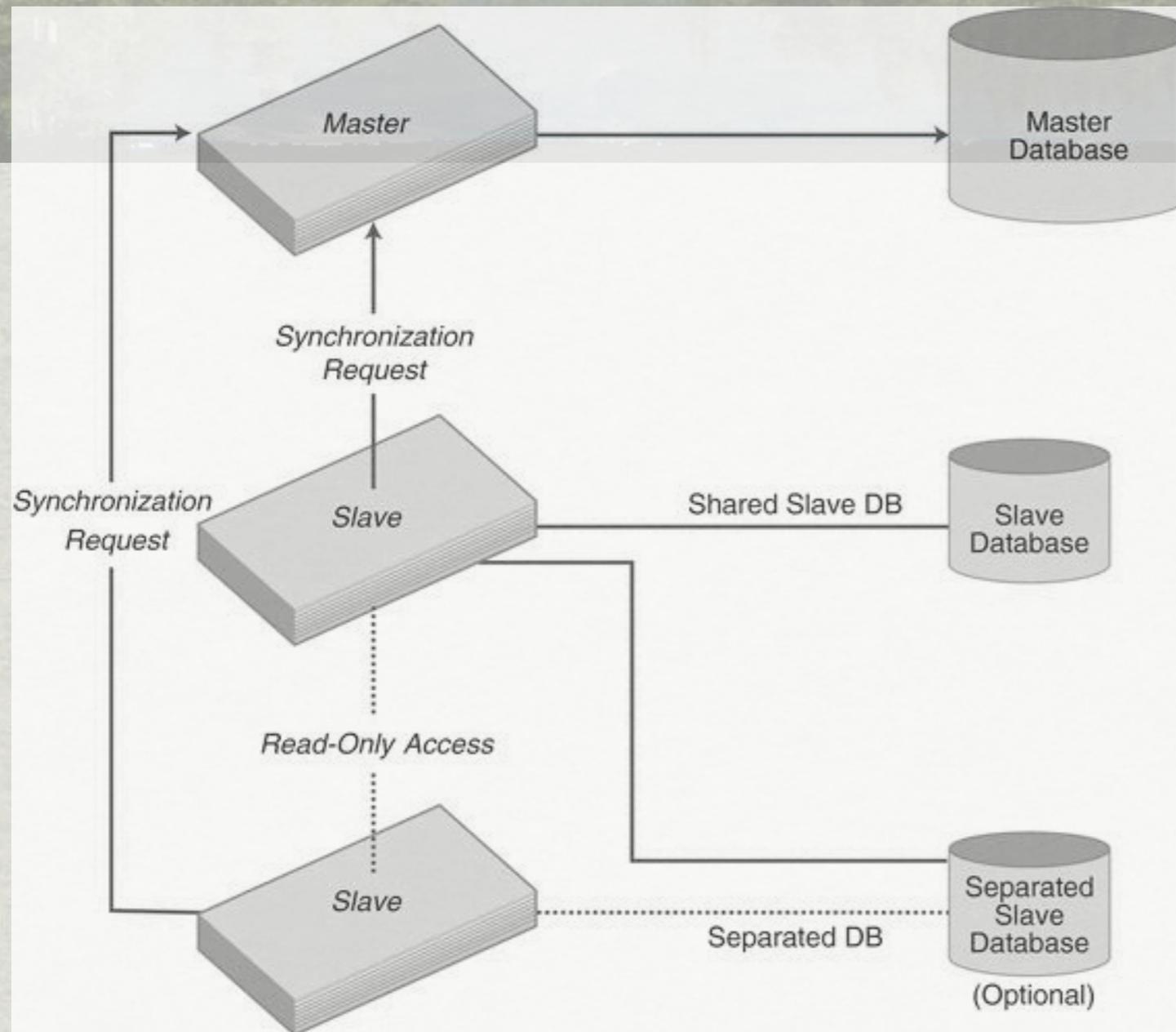
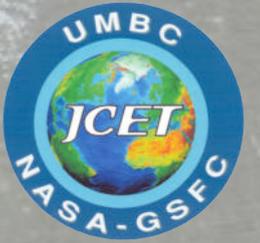
Parallel Data Queries (MPI2)



Increase performance

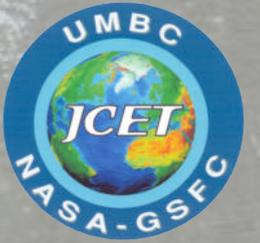


Parallel Database Cluster

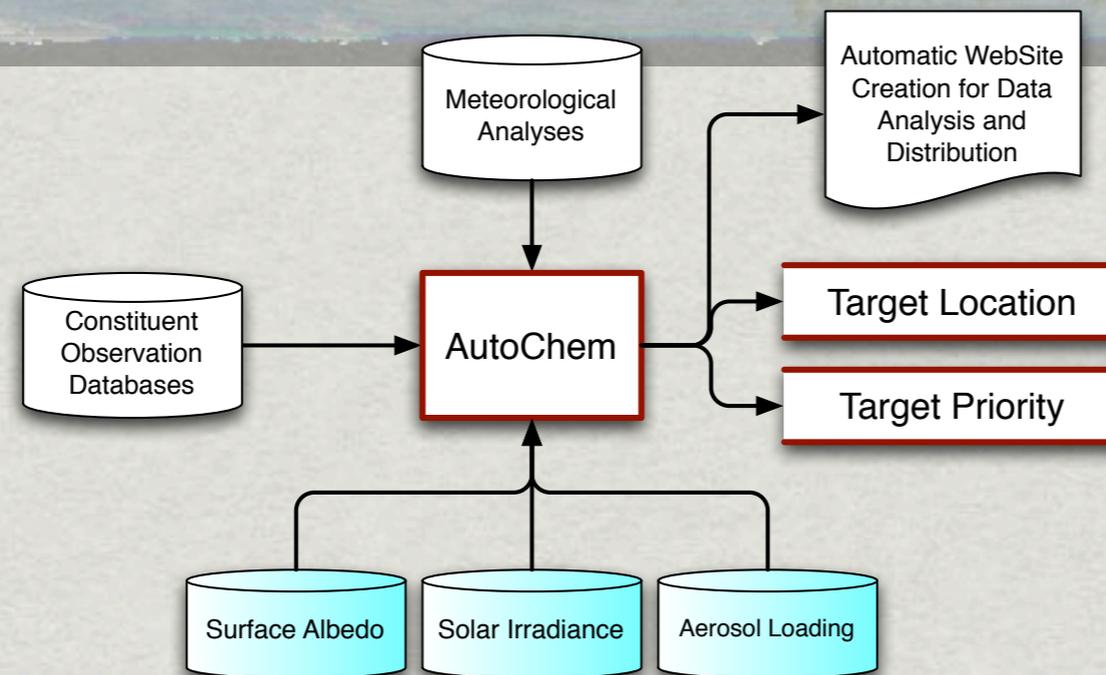


Increase performance

AutoChem Plug-in

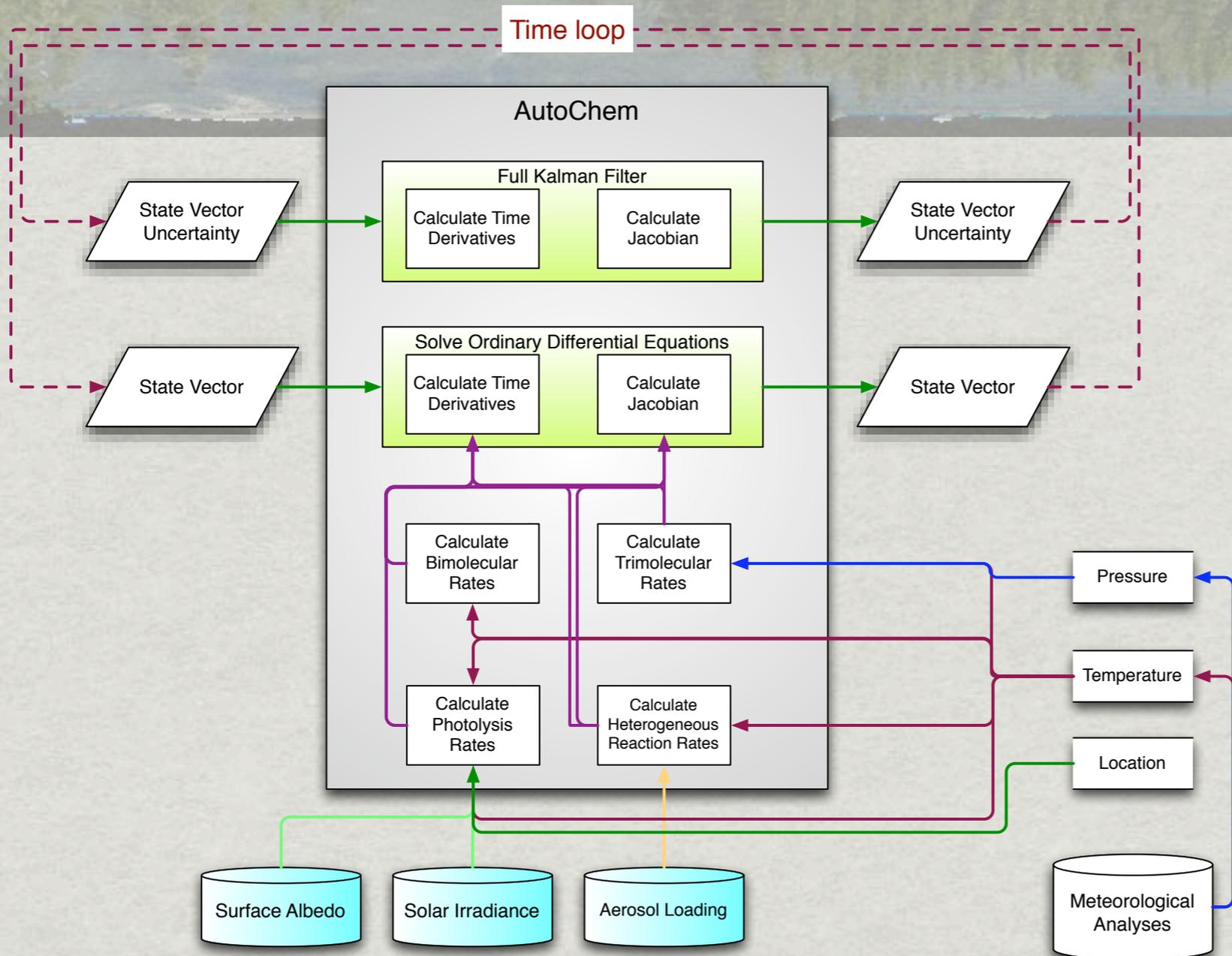
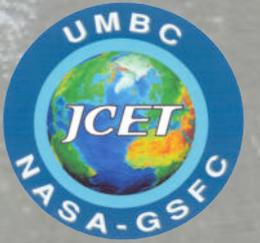


What we know from theory



ESMF Component

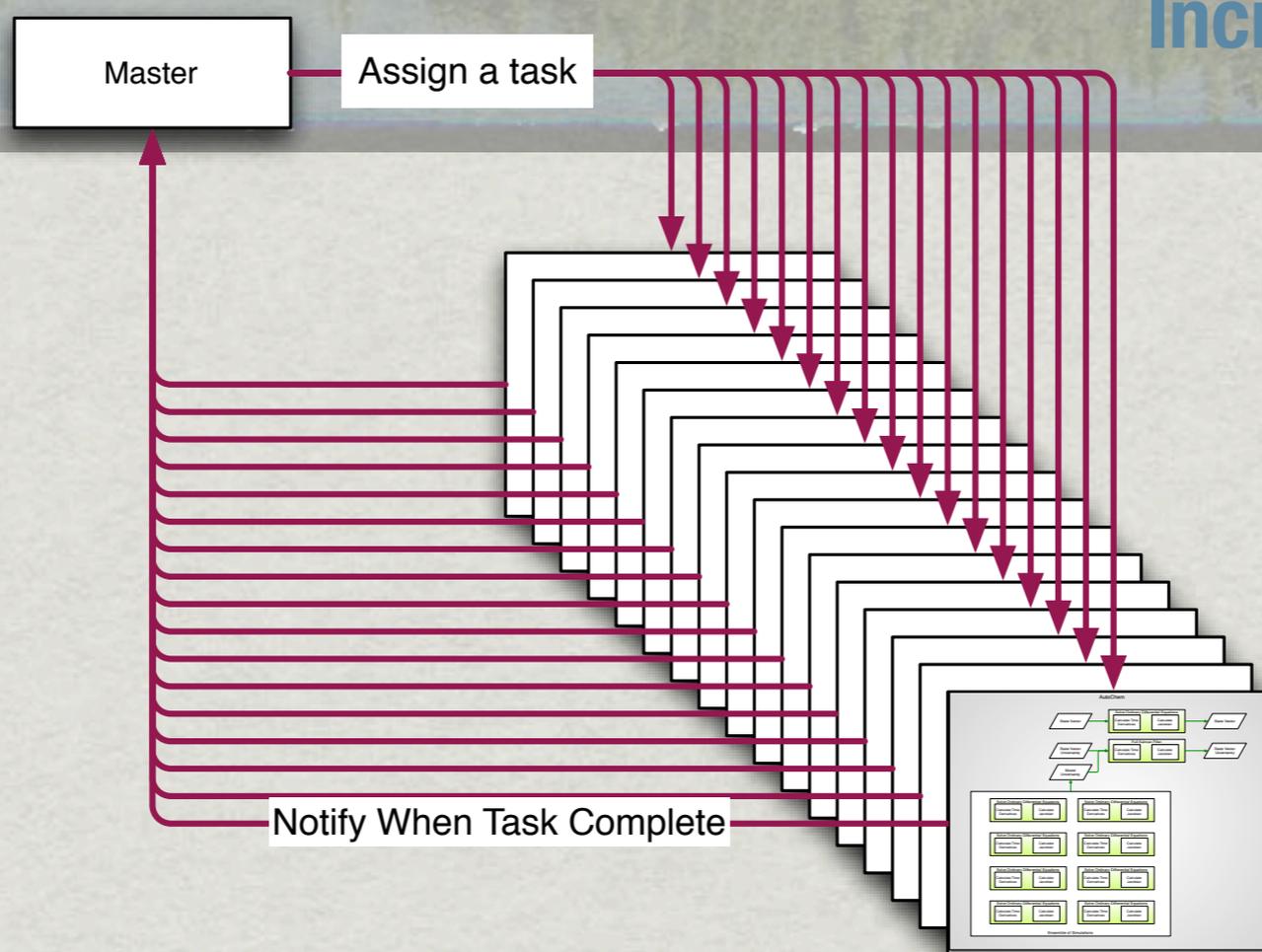
AutoChem Component



AutoChem Ensemble

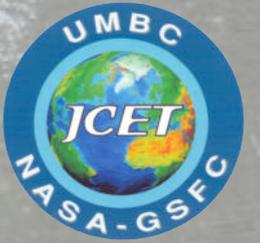


Increase performance

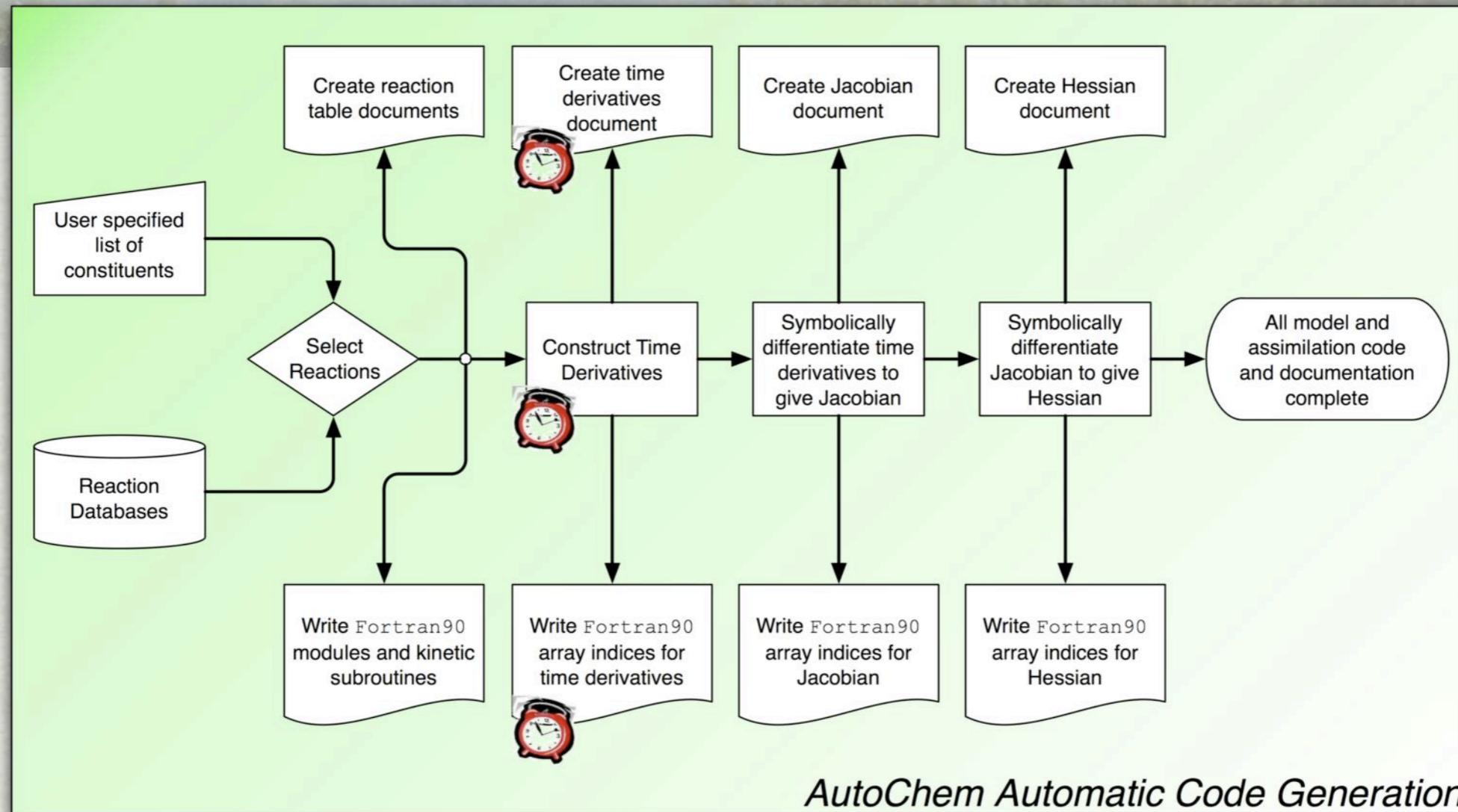


Like the database queries, the AutoChem system is also implemented in a Massively Parallel way using a master slave architecture.

Automatic Code Generation

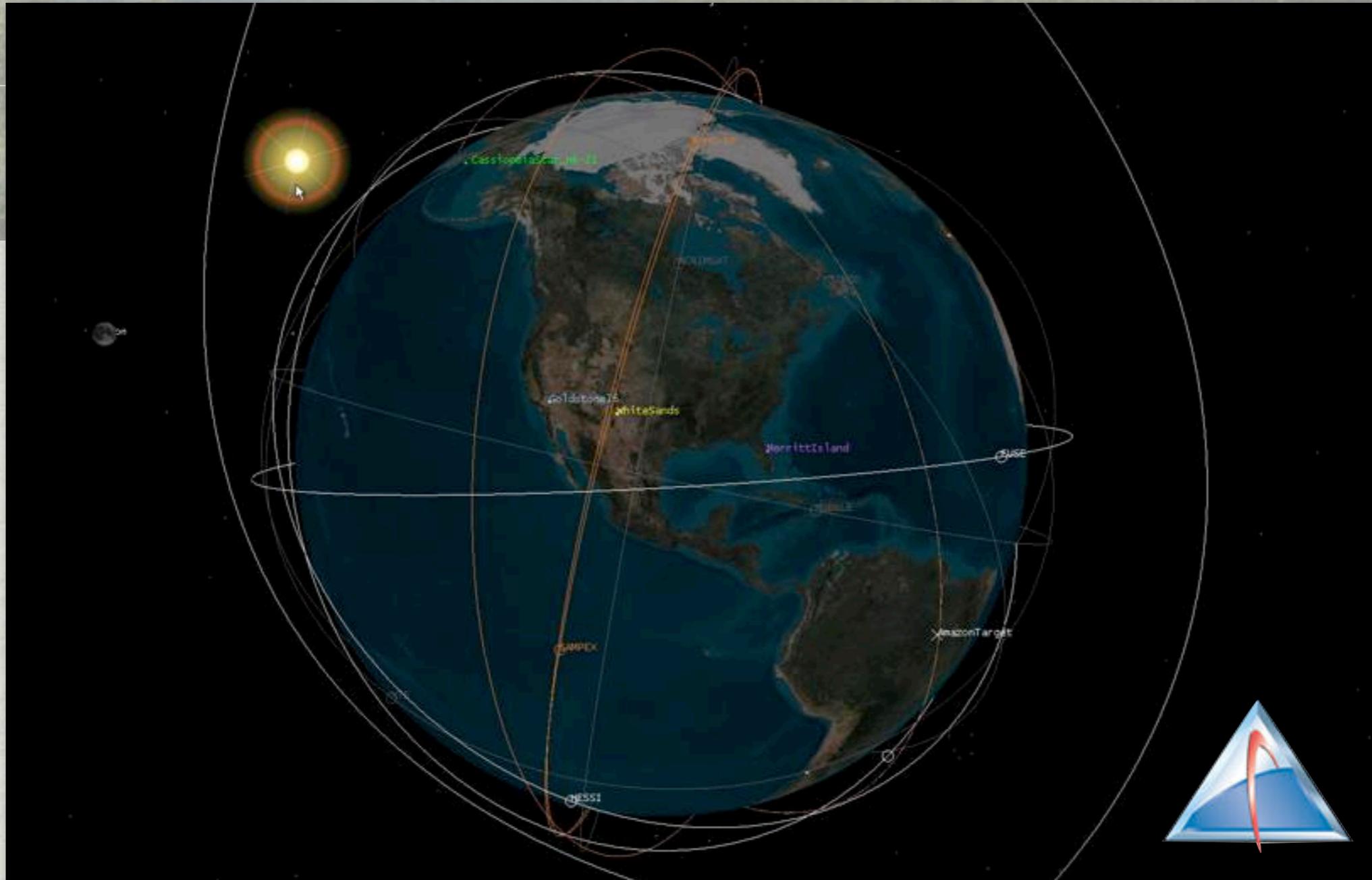


The model can automatically rewrite itself!



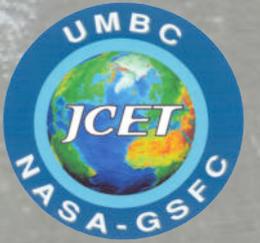
Engineering Diagram for AutoChem Code Generation

Sensor Web Simulator



Many Assets & Many Targets

Target Assignment: Multiple Modes



- Various modes depending on situation
- During a **validation** period (e.g. for the new decadal survey missions) we may want to target regions where we know the state of the system with the highest precision for our validation. In this case we would use targets defined by the **minima in our state vector uncertainty**.
- Conversely, during routine operation we would like the observing system to be adaptively reducing the total uncertainty, so would use targets defined on the **maxima in our state vector uncertainty**.
- It may be of use to have **feature recognition** as part of the targeting. For example, we may be focusing on ship tracks, or jet streaks in the weather systems.

Feature Recognition

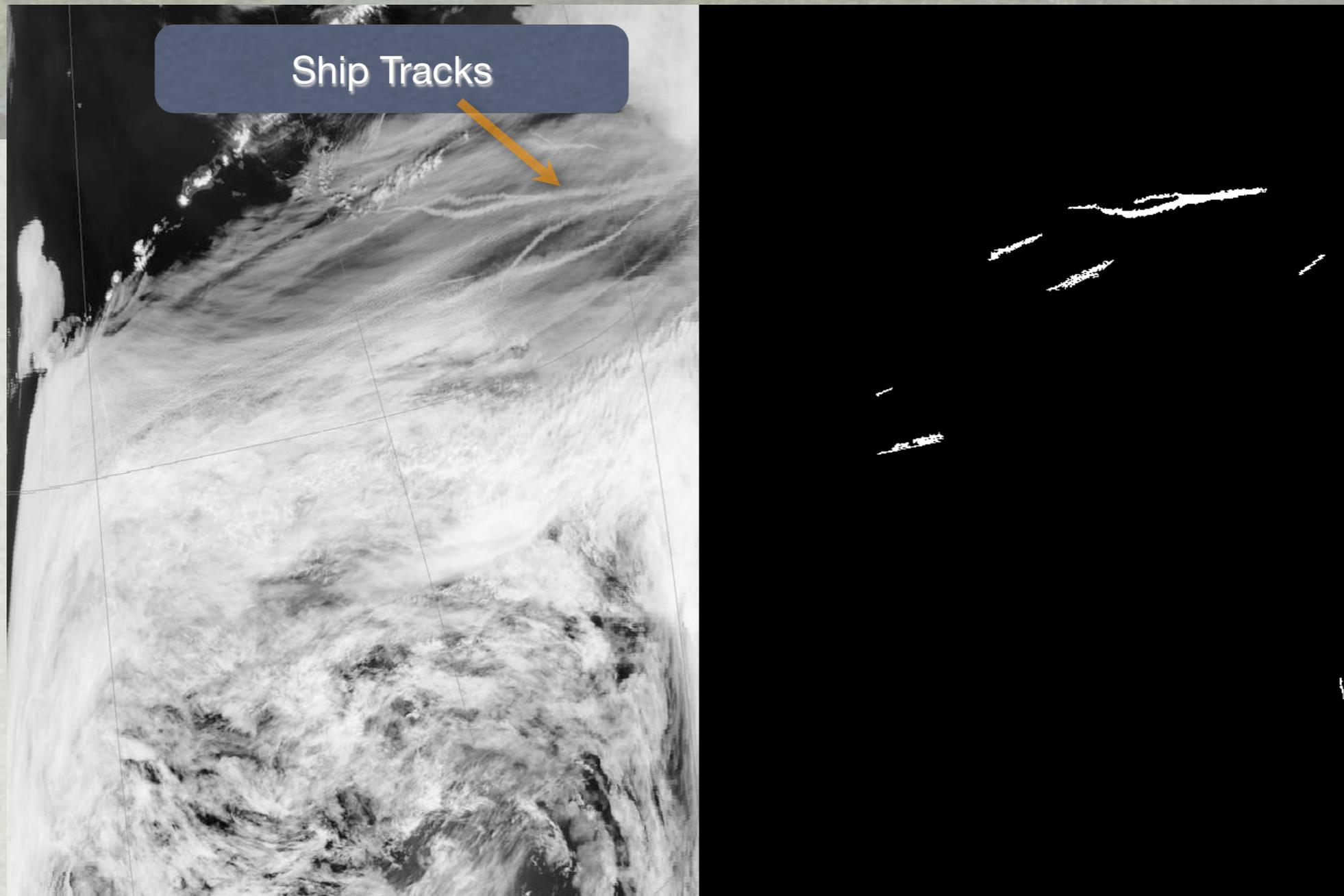
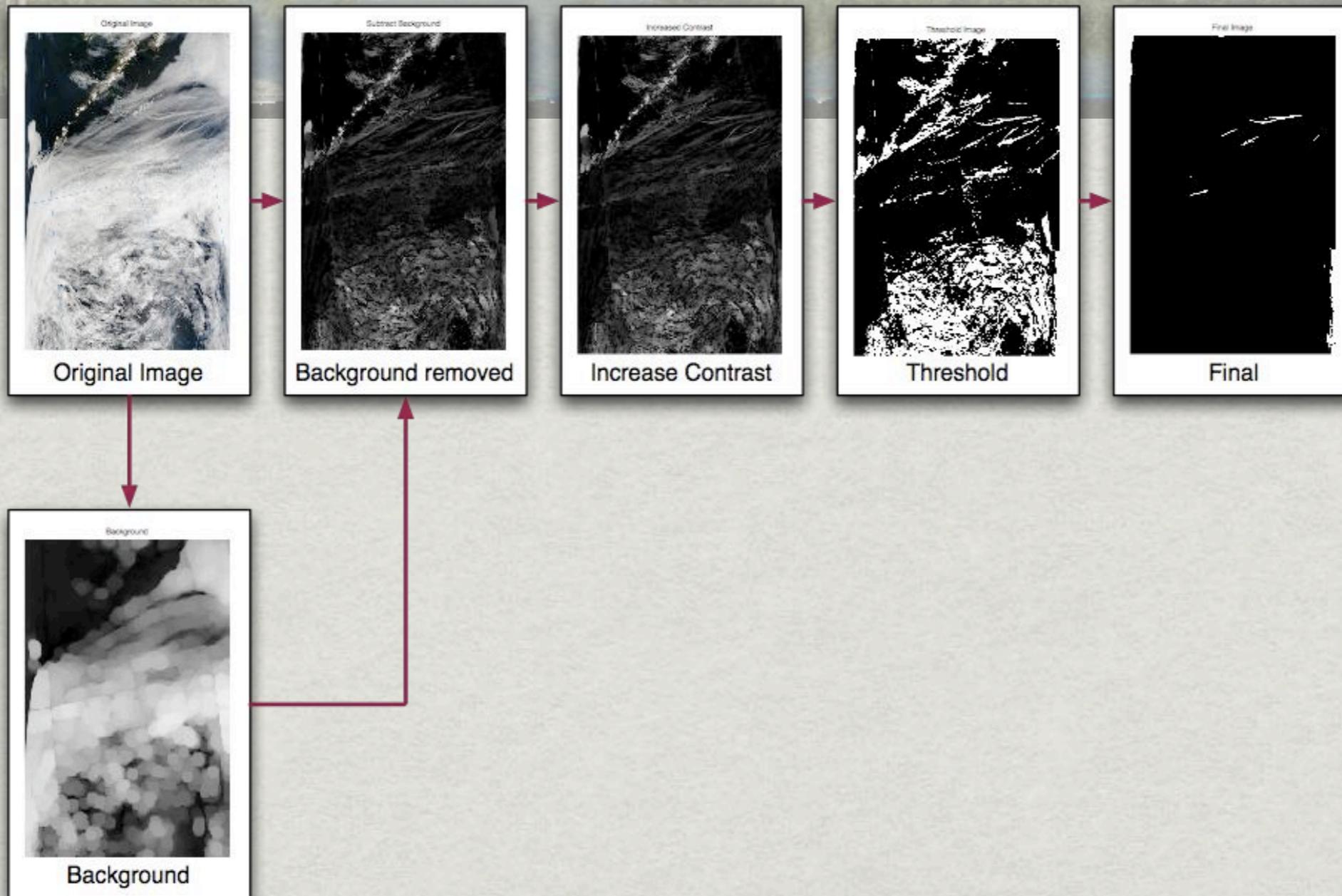
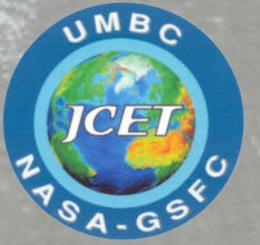
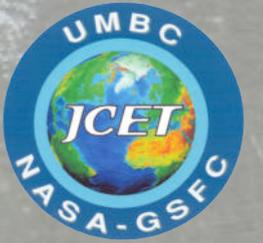


Image Processing Steps



Information Content



- To make best use of any observing system it is useful to construct a **ranked list** of variables/constituents that characterizes their **information content**. This list is obviously a function of the question asked as well as time and location.
- One example of such an index could be based on answering the question, in going from time t to time $t+\Delta t$ what are the key chemical players?
- The photochemical box model M describes the transformation of vector x from time t to time $t+\Delta t$.

$$x_{(t+\Delta t)} = M(t, x_t)$$

Information Content

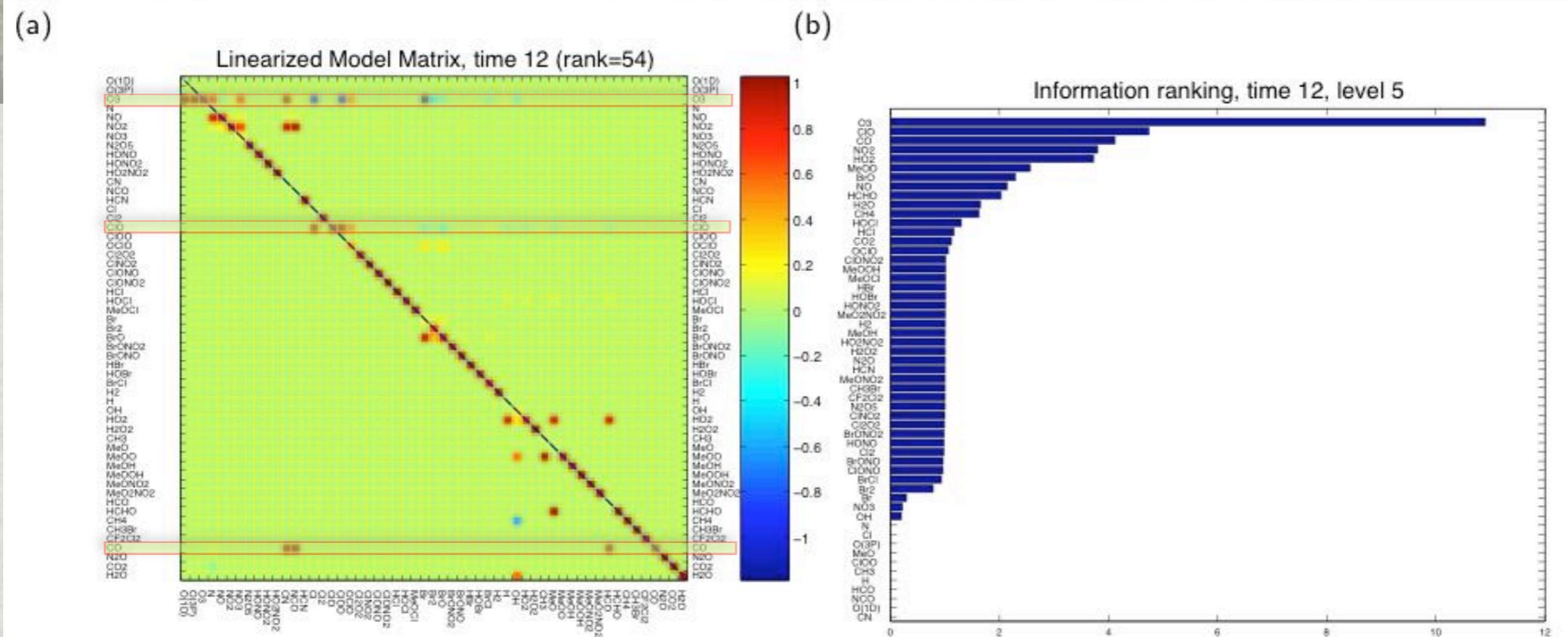
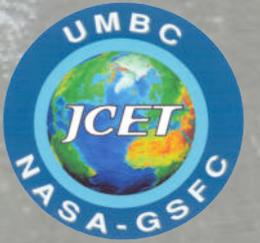
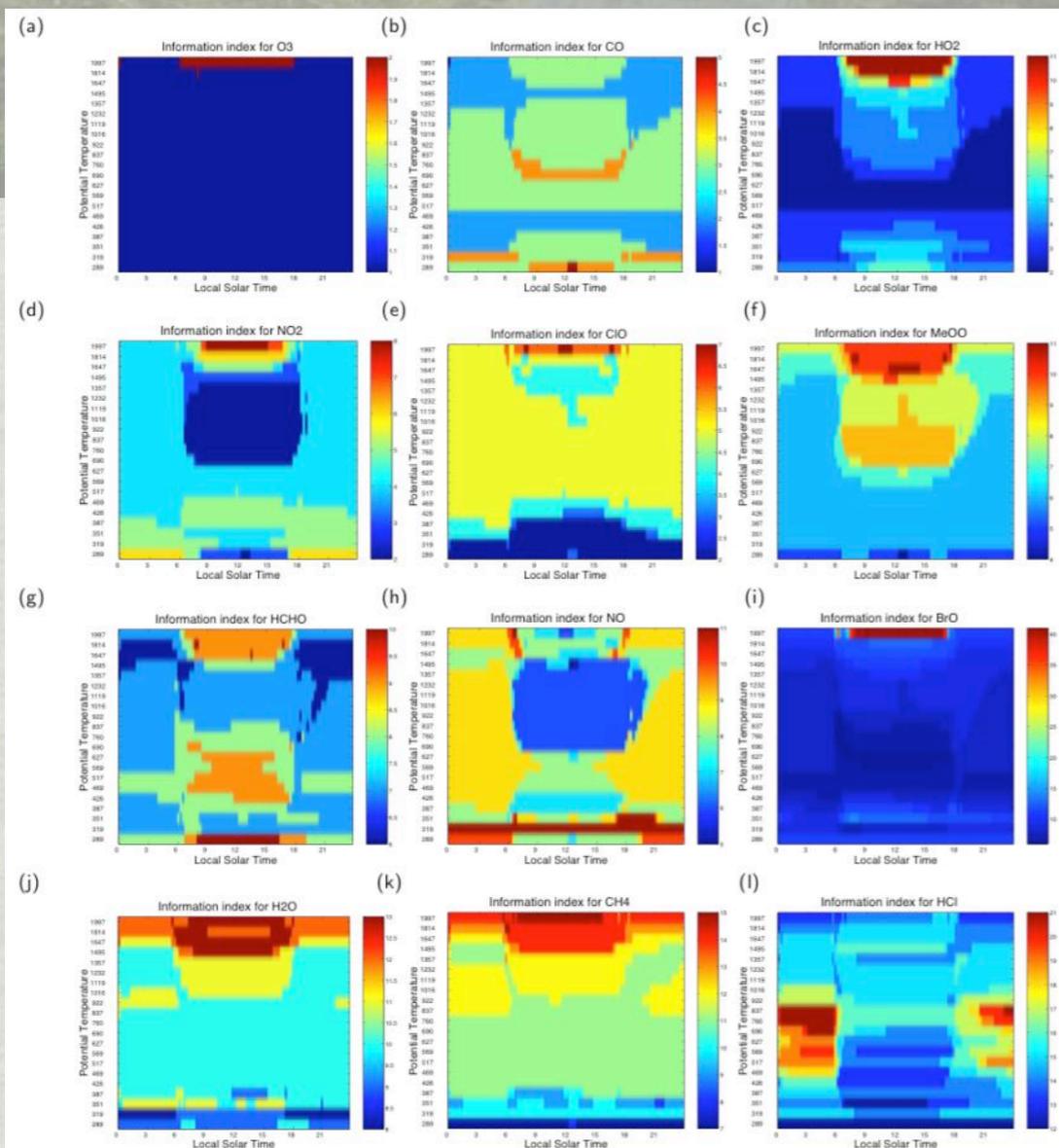
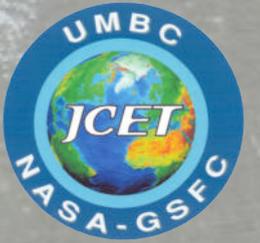


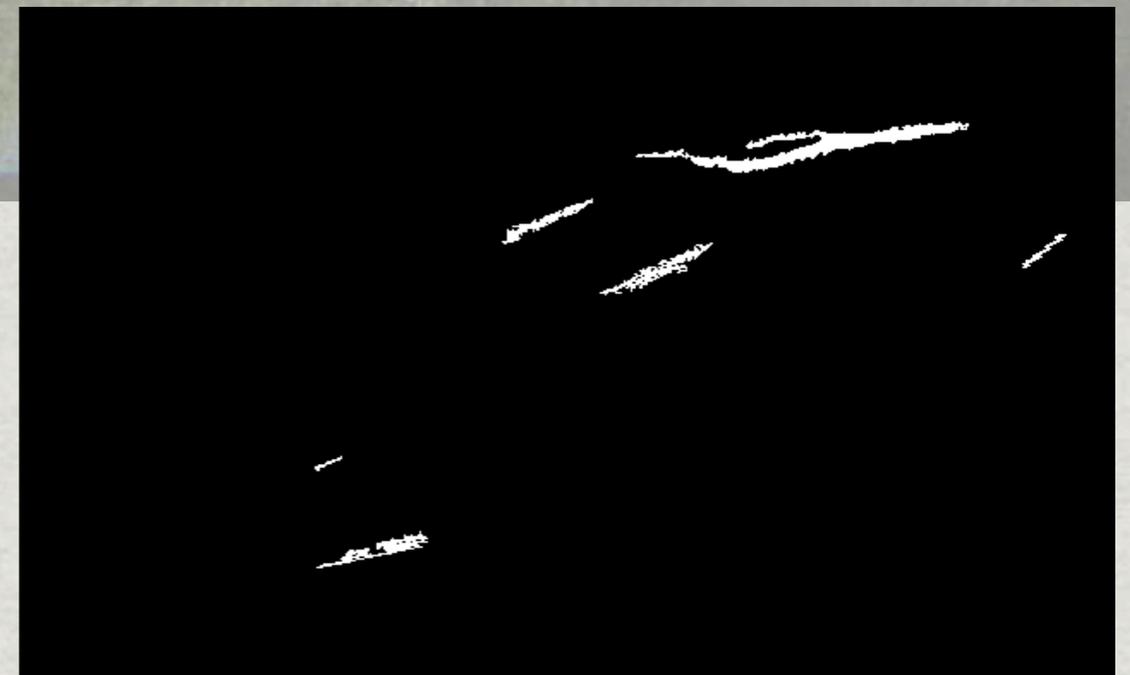
Figure (a) shows the linearized model matrix for a local solar time 12:15 at a potential temperature of 426 K (≈ 18 km) on 30 March 1992 at 38°S. (b) shows the chemical information content index, I_c .

$$x_{(t+\Delta t)} = M(t, x_t)$$

Hybrid Mode



The chemical information content changes with time and location. The panels show some examples of how the information index changes with time (at 15 minute intervals) and location in a vertical profile at 38°S.

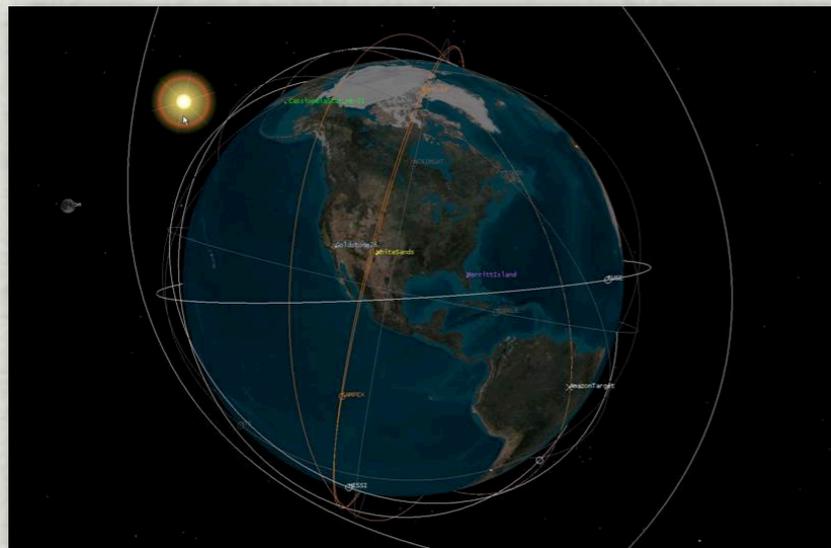


- Imagine a hybrid mode where we use:
 - feature recognition
 - information content

Scheduling Autonomy

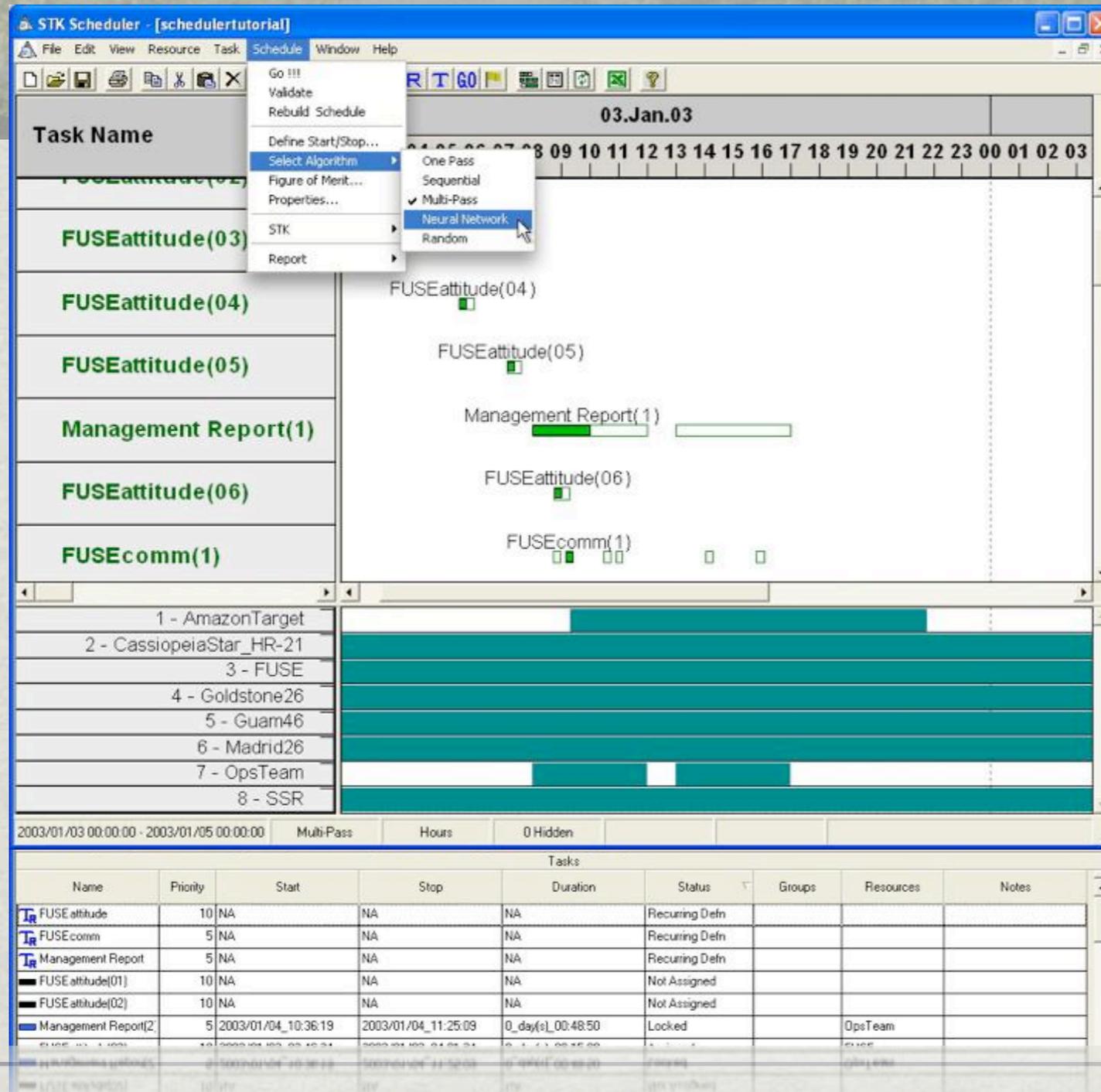


- So our autonomy has reduced to objectively **choosing our targets** and for each target objectively **choosing a priority**.
- All that remains is to see if our observing sensor web is **capable** of observing these targets. For this we use STK and Scheduler

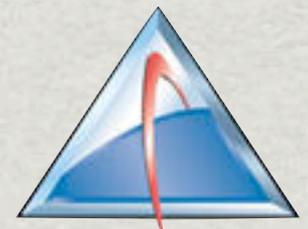


Many Assets & Many Targets

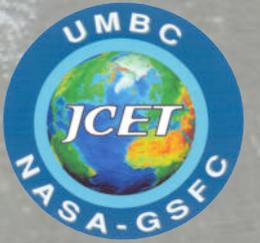
Scheduler Results



- Power
- Communication
- Bandwidth
- Memory

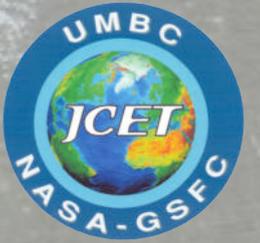


Genetic Algorithms

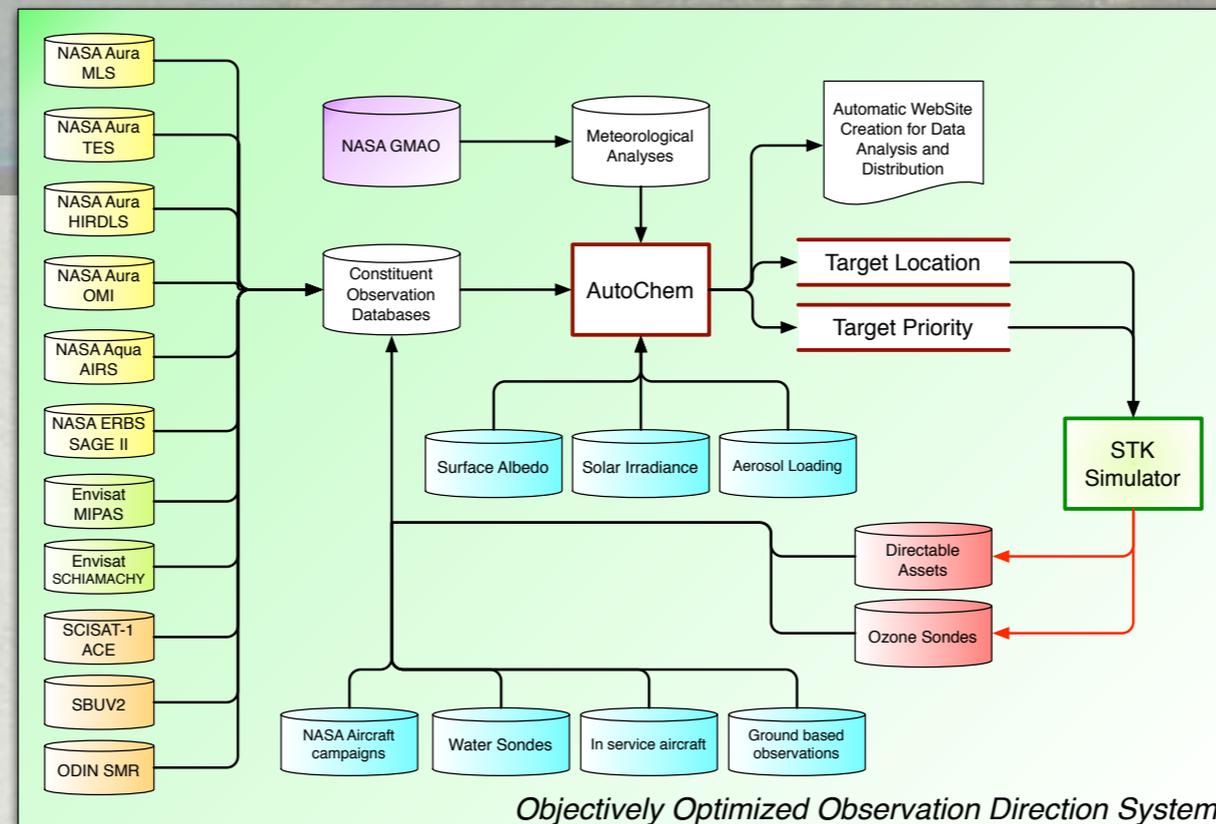
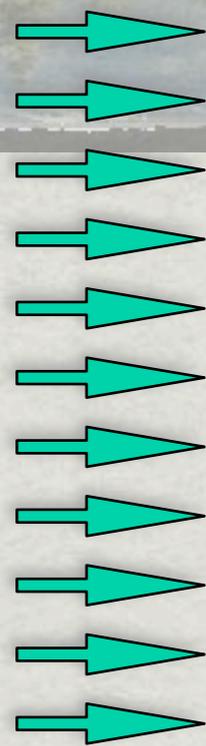


- A genetic algorithm is a search technique used in computing to find true or approximate solutions to optimization and search problems.
- Genetic algorithms are a particular class of evolutionary algorithms that use techniques inspired by biological inheritance, mutation, selection, and crossover (also called recombination).
- The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population.
- The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

Dealing With Biases



Many Sources of Data



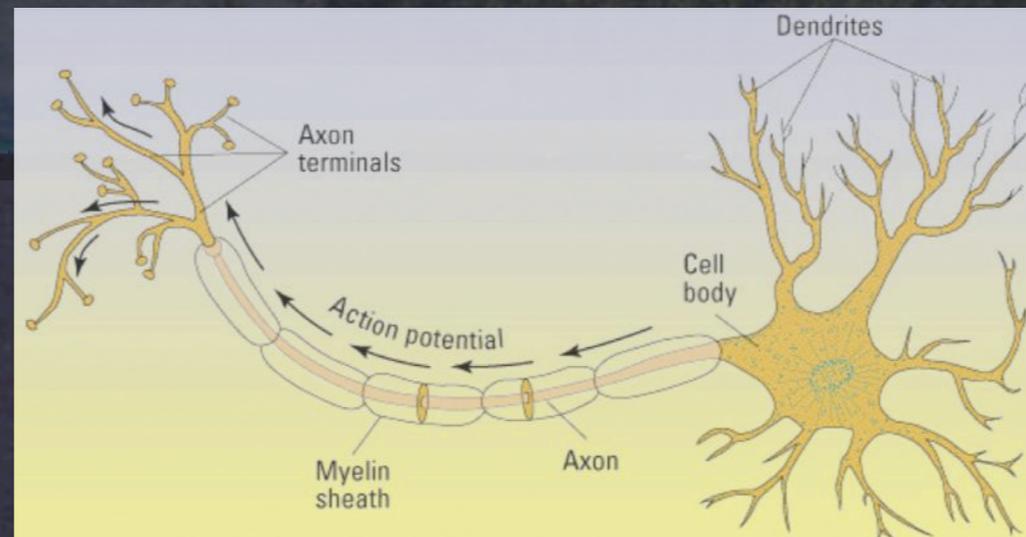
Modeling and Assimilation System Engineering Diagram.

- Almost by definition data **biases** are going to be an issue with sensor webs as we are fusing data from so many sources.



Biases are ubiquitous. When combining observations from many sensors over a long time period biases will always be an issue.

If they are not dealt with they hinder us addressing the scientific issues the measurements were taken to address (as the next set of slides illustrate).



Variations in Stratospheric Cly Between 1991 and the present

- Data can be biased, maybe as a function of many parameters.
- May be observing a proxy for what we really want to know.

Constrained by a limited number of Cl_y observations

A large range of Cl_y in the model simulations



21st CENTURY OZONE LAYER

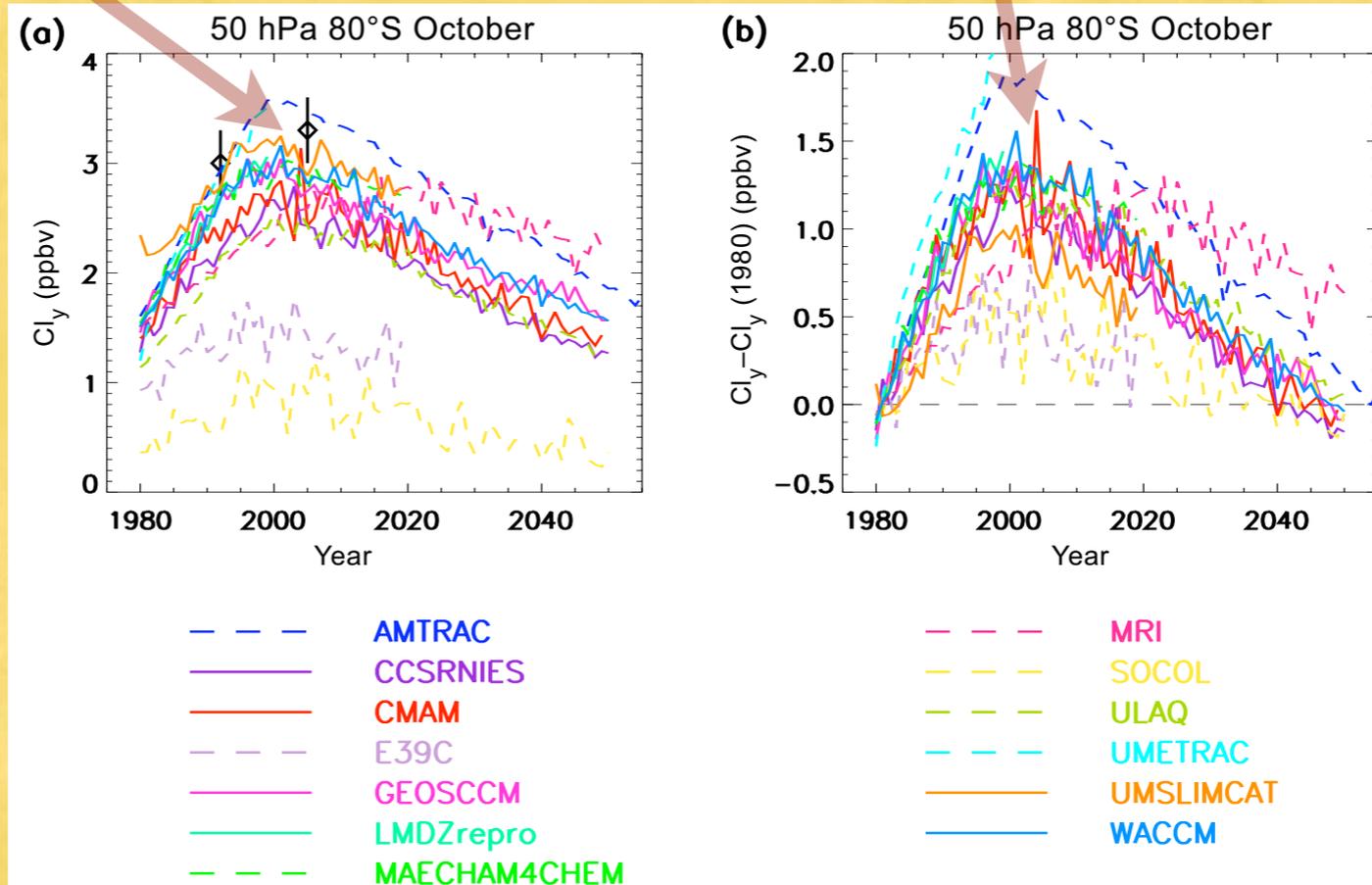
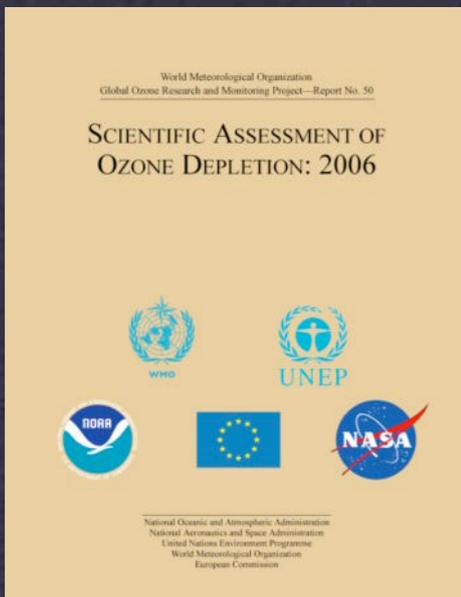
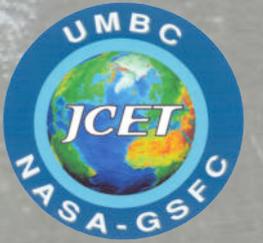


Figure 6-8. October zonal mean values of total inorganic chlorine (Cl_y in ppb) at 50 hPa and 80°S from CCMs. Panel (a) shows Cl_y and panel (b) difference in Cl_y from that in 1980. The symbols in (a) show estimates of Cl_y in the Antarctic lower stratosphere in spring from measurements from the UARS satellite in 1992 and the Aura satellite in 2005, yielding values around 3 ppb (Douglass et al., 1995; Santee et al., 1996) and around 3.3 ppb (see Figure 4-8), respectively.



Why we need the data



- We need to know the distribution of inorganic chlorine (Cl_y) in the stratosphere to:
 - Attribute changes in stratospheric ozone to changes in halogens.
 - Assess the realism of chemistry-climate models.

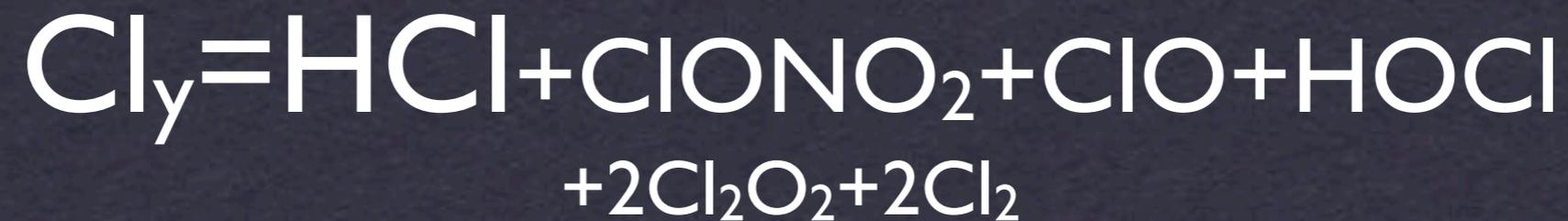


Long time-series

Long time-series

Sporadic

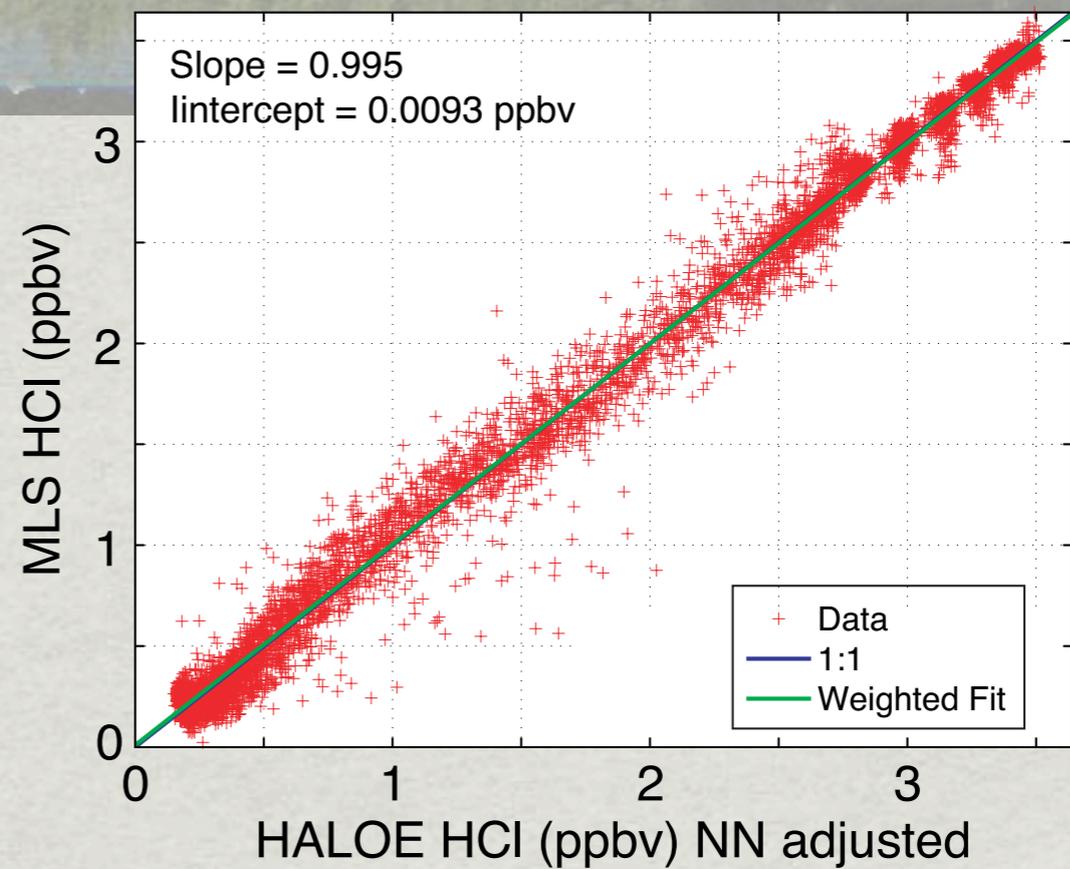
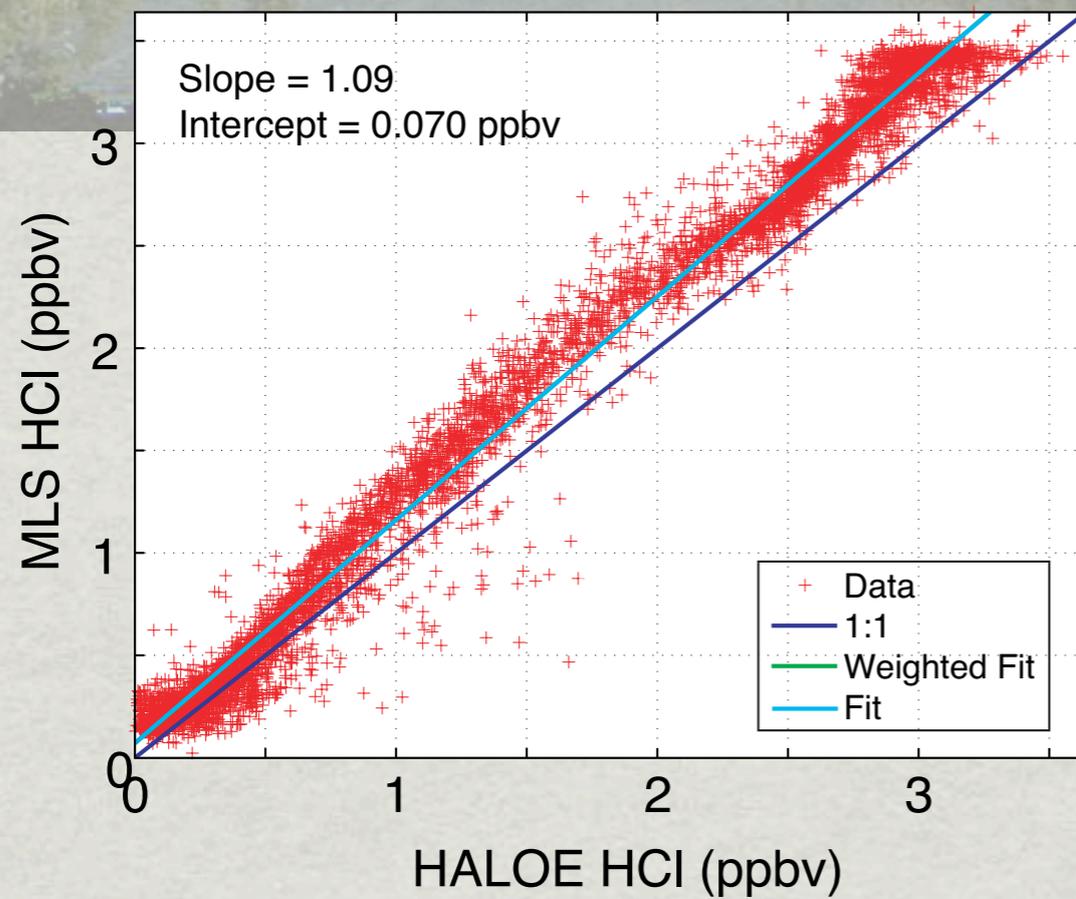
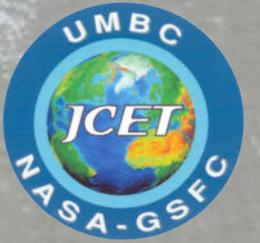
Since 2004



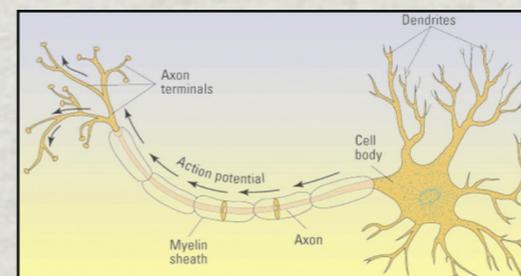
Estimating Cl_y is hampered by lack of observations

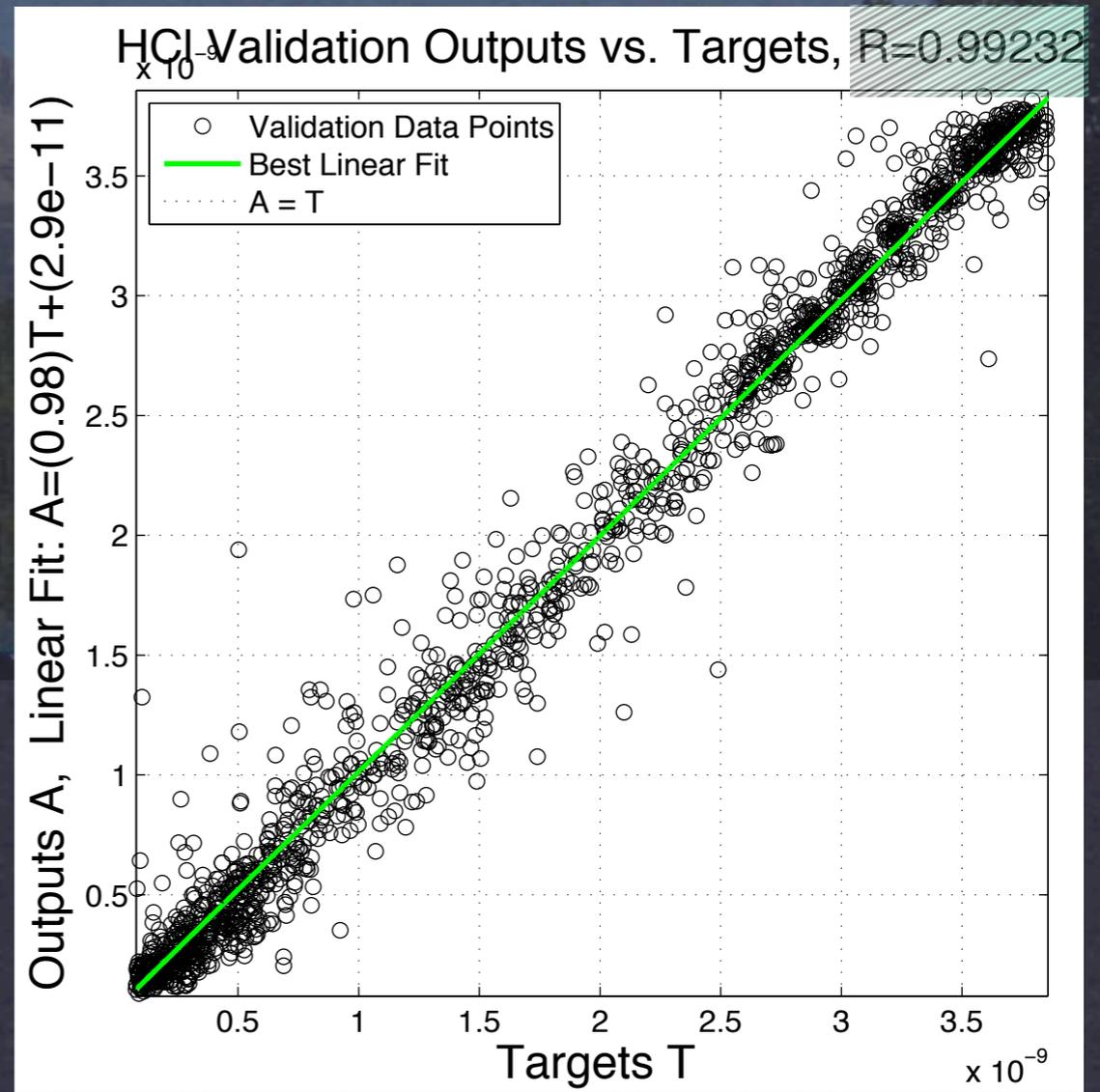
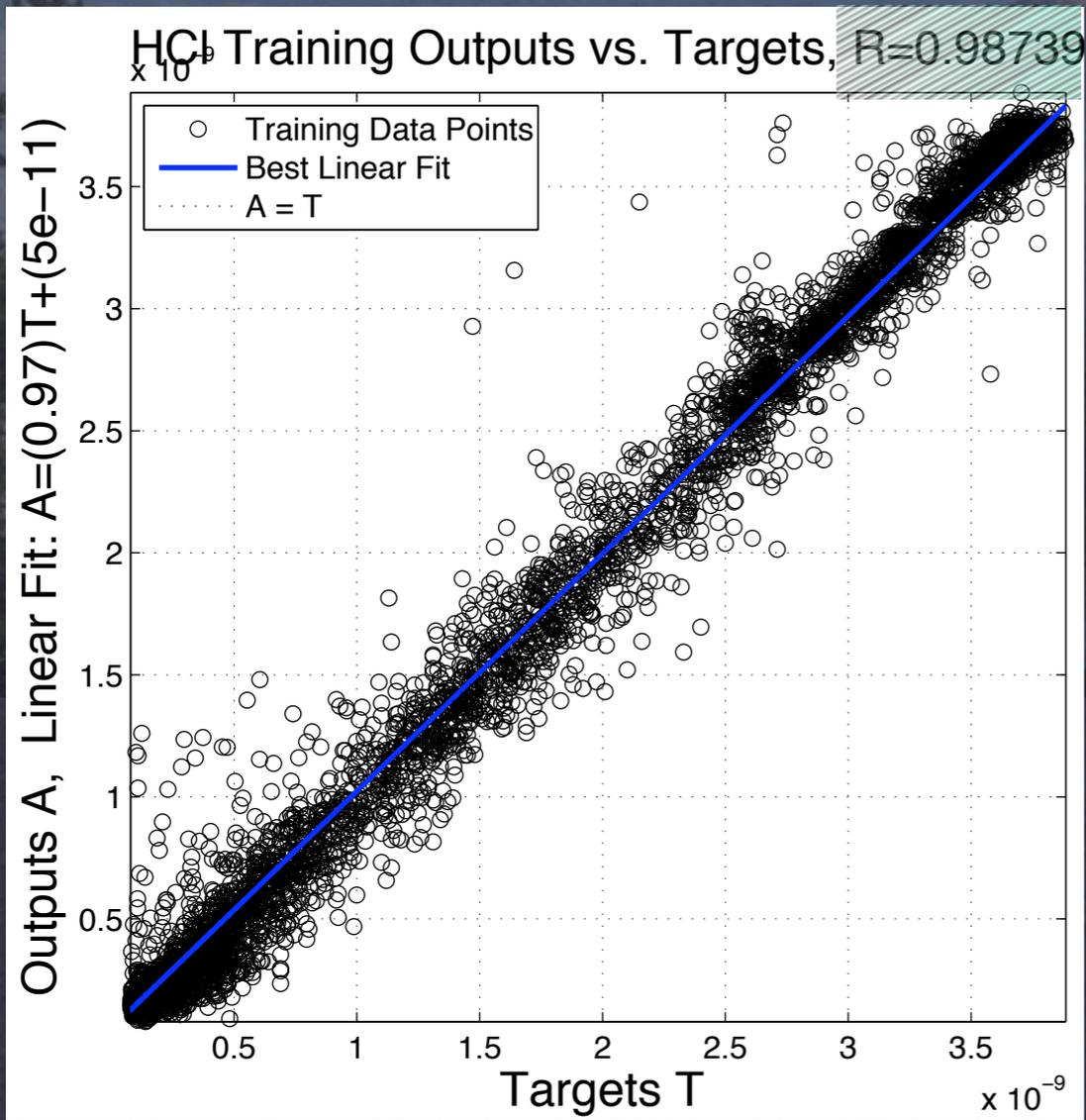
Estimating Cl_y is hampered by inter-instrument biases

HCl Inter-comparisons

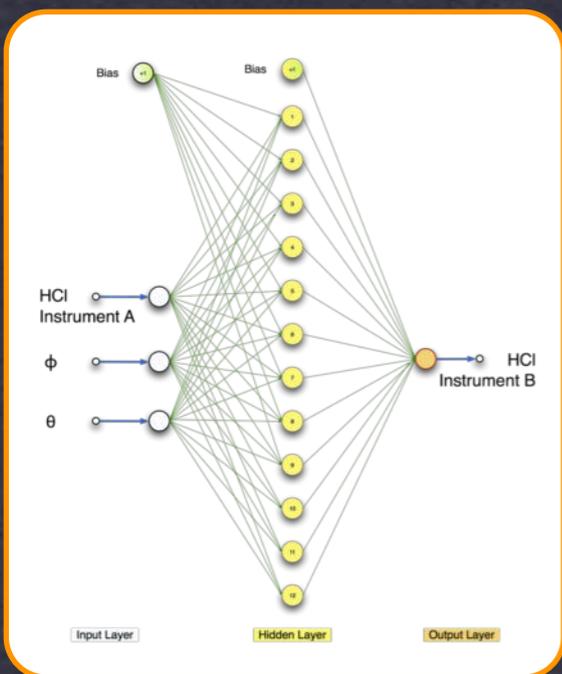


Global Scatter Diagram

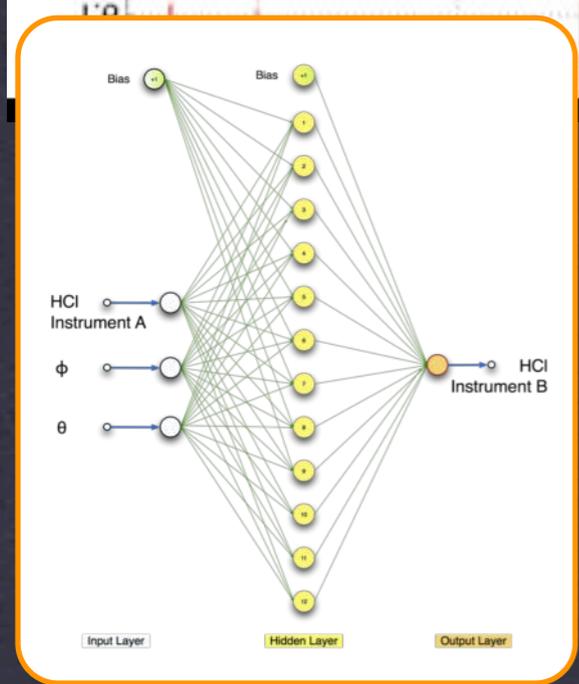
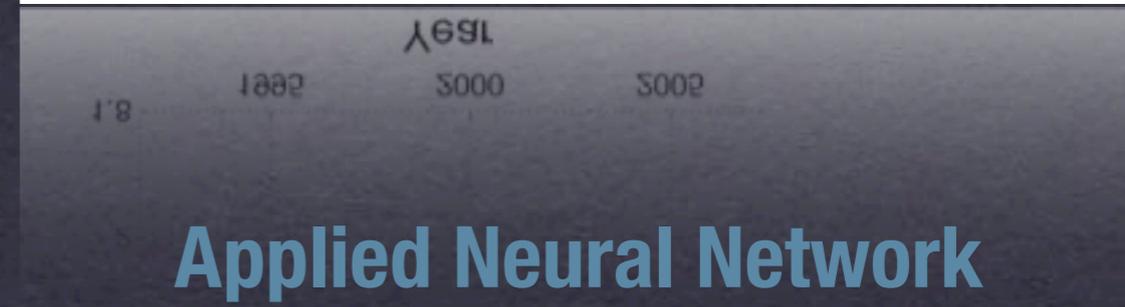
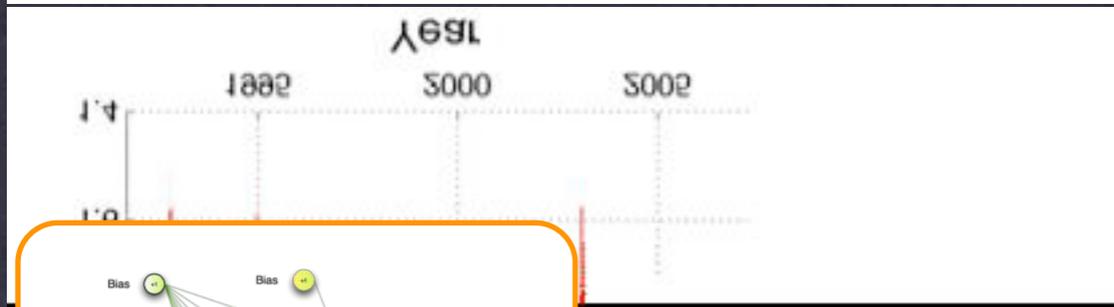
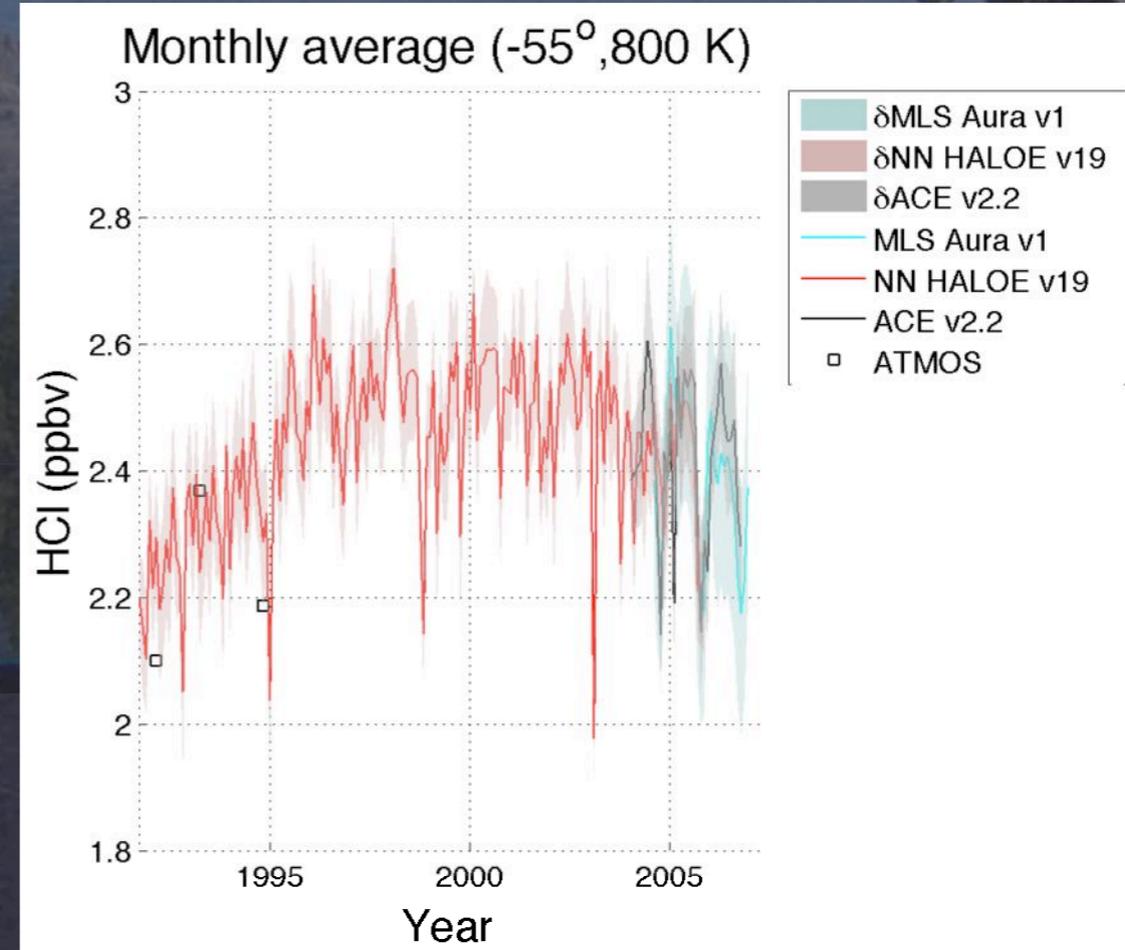
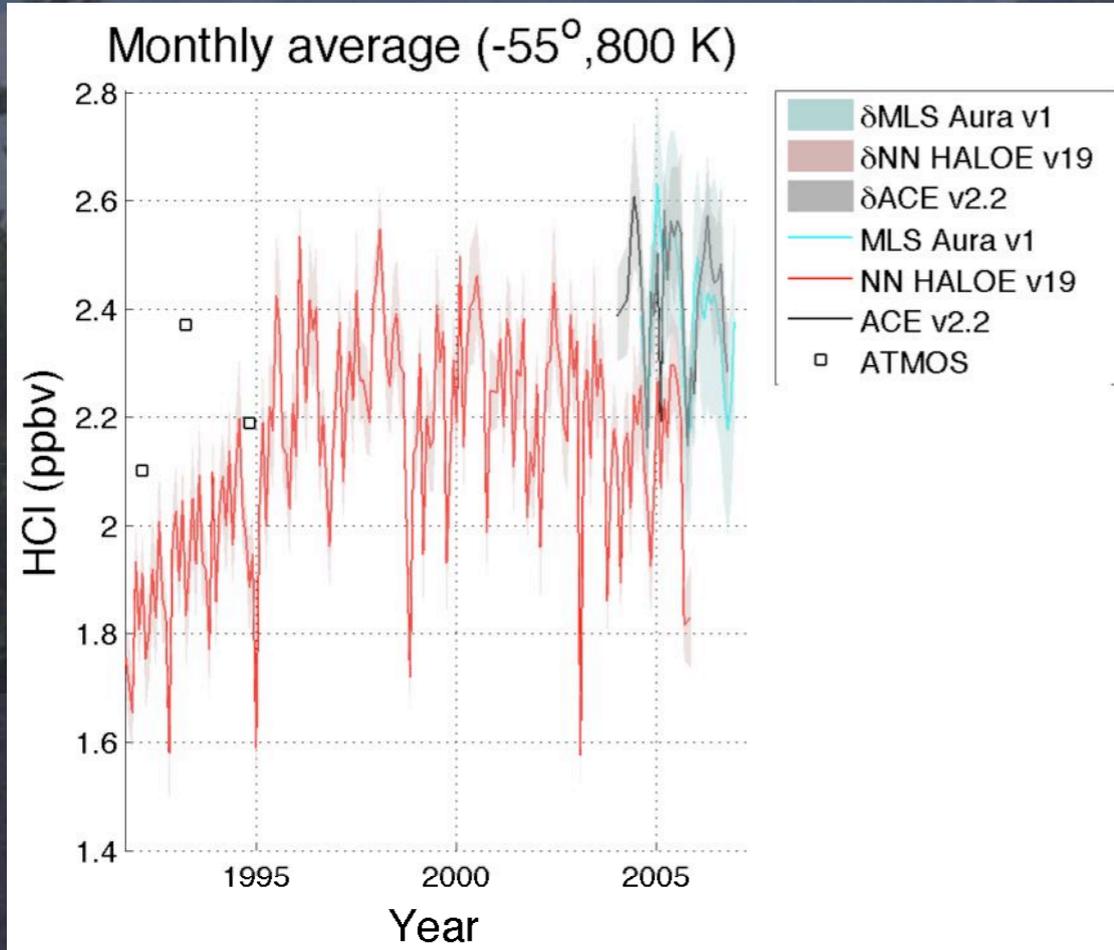




Totally independent validation



Re-calibration using a Neural Network



Applied Neural Network
Re-calibration to HALOE

Long-term continuity

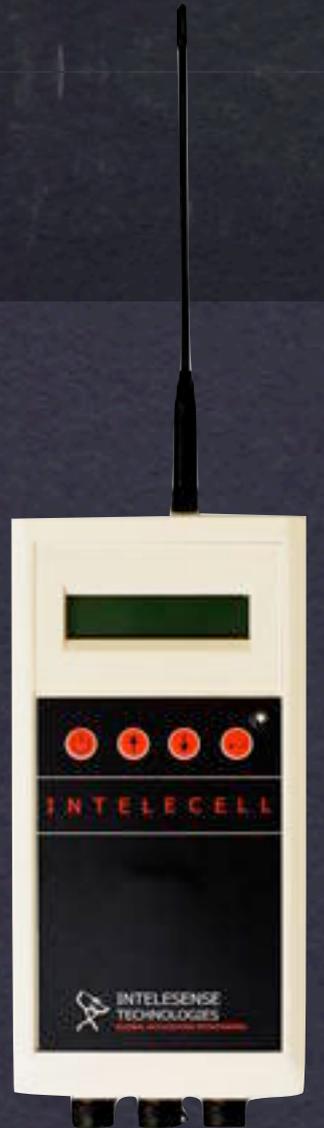
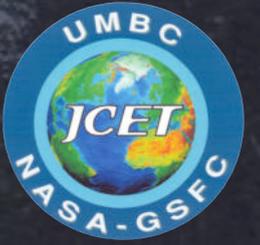
Future Possibilities

Simulation courtesy of Jay Boris NRL

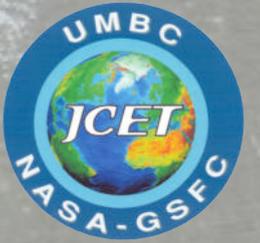
Source Location: Times Square
Elapsed Time: 6 Minutes



Looking Ahead



Educational Aspects



- Two graduate students:

- Oleg Aulov (PhD), registered at the University of Maryland Baltimore County for a PhD in Computer Science and funded from this proposal. Oleg has been working on the STK aspects of this project.
- Andrew Rickert (MSc), registered at the University of Maryland Baltimore County for a MSc in Physics. Andy has been working on some of the neural network aspects of this project.



Summary



- Autonomous target selection based on:
 - Objective measures, such as state vector uncertainty (what do we need to know?)
 - Image processing, feature recognition
- Autonomous target priority based on:
 - Information content (how useful is the observation?)
- Hybrid Modes
- Smart scheduler aware of sensor web's capabilities
- **Biases are always going to be an issue, let us deal with them.**
- Objectively **optimized design** using genetic algorithms.